In this talk, we introduce an enhanced version of the incremental singular value decomposition (SVD) method . The original incremental SVD, proposed by Brand, efficiently computes the SVD of a matrix by iteratively updating a sequence of orthogonal transformations. However, the accumulation of such transformations can degrade orthogonality, necessitating frequent and computationally expensive reorthogonalizations. Brand raised the open question of how often reorthogonalization is required to ensure numerical precision. In this talk, we first answer this question by presenting a modified algorithm that entirely avoids computing large numbers of intermediate orthogonal matrices.

We further apply this modified incremental SVD technique to the numerical solution of Non-Fickian flows, a class of problems where the current solution depends on all previous time steps. This temporal dependency results in a linearly growing memory footprint and a quadratically increasing computational cost. Assuming the solution data is approximately low-rank, we introduce a memory-free algorithm based on incremental SVD that maintains only linear growth in computational complexity with respect to the number of time steps. We show that the solution error introduced by our approach is within machine precision, and our numerical results affirm significant gains in both computational efficiency and memory usage.